ENHANCED CONTEXT-AWARE FRAMEWORK FOR INDIVIDUAL AND CROWD CONDITION PREDICTION

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DEDICATION

To the Almighty Allah who made it possible from the beginning to the end.

To Prophet Muhammad and His Companions.

To my late Mother (Simbiat) and my mother inlaw (Khadijat Olaoye) Innalillahi Wainailei Rojiuna, My Father (Suleiman) and My late foster brother Gbenga Valentine Arowopayin (RIP) whose sad event caught me unaware on the black morning of March 26, 2019.

To my brothers and sisters.

To my beloved wife, Muibat Arike.

To my lovely children (Muhammad, Abdullateef, Fawaz, and Maryam)

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ABSTRACT

Context-aware framework is basic context-aware that utilizes contexts such as user with their individual activities, location and time, which are hidden information derived from smartphone sensors. These data are used to monitor a situation in a crowd scenario. Its application using embedded sensors has the potential to monitor tasks that are practically complicated to access. Inaccuracies observed in the individual activity recognition (IAR) due to faulty accelerometer data and data classification problem have led to its inefficiency when used for prediction. This study developed a solution to this problem by introducing a method of feature extraction and selection, which provides a higher accuracy by selecting only the relevant features and minimizing false negative rate (FNR) of IAR used for crowd condition prediction. The approach used was the enhanced context-aware framework (EHCAF) for the prediction of human movement activities during an emergency. Three new methods to ensure high accuracy and low FNR were introduced. Firstly, an improved statistical-based time-frequency domain (SBTFD) representing and extracting hidden context information from sensor signals with improved accuracy was introduced. Secondly, a feature selection method (FSM) to achieve improved accuracy with statistical-based time-frequency domain (SBTFD) and low false negative rate was used. Finally, a method for individual behaviour estimation (IBE) and crowd condition prediction in which the threshold and crowd density determination (CDD) was developed and used, achieved a low false negative rate. The approach showed that the individual behaviour estimation used the best selected features, flow velocity estimation and direction to determine the disparity value of individual abnormality behaviour in a crowd. These were used for individual and crowd density determination evaluation in terms of inflow, outflow and crowd turbulence during an emergency. Classifiers were used to confirm features ability to differentiate individual activity recognition data class. Experimenting SBTFD with decision tree (J48) classifier produced a maximum of 99.2% accuracy and 3.3% false negative rate. The individual classes were classified based on 7 best features, which produced a reduction in dimension, increased accuracy to 99.1% and had a low false negative rate (FNR) of 2.8%. In conclusion, the enhanced context-aware framework that was developed in this research proved to be a viable solution for individual and crowd condition prediction in our society.

ABSTRAK

Rangka kerja kesedaran-konteks adalah kerangka kerja asas kesedaran-konteks yang menggunakan konteks seperti pengguna dengan aktiviti individu mereka, lokasi dan masa yang merupakan maklumat tersembunyi yang diperoleh dari sensor telefon. Data ini digunakan untuk memantau keadaan dalam senario kelompok manusia. Aplikasinya menggunakan sensor terbenam mempunyai potensi untuk memantau tugasan yang secara praktikalnya sukar untuk diakses. Ketidaktepatan yang dihasilkan dalam aktiviti pengecaman individu (IAR) disebabkan masalah peranti meter-kepecutan dan masalah pengklasifikasian data telah menyebabkan kesan kepada ketidakcekapan peramalan. Kajian ini mengemukakan penyelesaian kepada masalah ini dengan memperkenalkan kaedah pengekstrakan dan pemilihan ciri-ciri yang menghasilkan ketepatan yang lebih tinggi dengan hanya memilih ciri-ciri yang berkaitan bagi mengurangkan kadar negatif palsu (FNR) bagi IAR yang digunakan untuk meramal keadaan kelompok manusia. Pendekatan yang digunakan adalah berdasarkan rangka kerja kesedaran-konteks (EHCAF) yang digunakan untuk meramal aktiviti pergerakan manusia semasa kecemasan. Tiga kaedah baru untuk memastikan ketepatan yang tinggi dan FNR yang rendah telah diperkenalkan. Pertama, penambahbaikan domain kekerapan masa berdasarkan statistik (SBTFD) yang mewakili dan mengekstrak maklumat konteks tersembunyi dari isyarat sensor dengan peningkatan ketepatan isyaratnya. Kedua, kaedah pemilihan ciri (FSM) dapat mencapai ketepatan yang lebih baik dengan domain kekerapan masa berdasarkan statistik (SBTFD) dan kadar negatif palsu yang rendah digunakan. Akhirnya, satu kaedah bagi ramalan tingkah laku individu (IBE) dan ramalan rempuhan manusia di mana ambang dan penentuan kepadatan kerumunan (CDD) telah dibangunkan dan digunakan, menghasilkan kadar negatif palsu yang rendah. Pendekatan menunjukkan bahawa pengiraan tingkah laku individu menggunakan ciri-ciri pengelasan terbaik, anggaran halaju aliran dan arah untuk menentukan nilai kelakuan abnormal individu dalam kelompok manusia. Ini digunakan untuk penilaian penentuan ketumpatan individu dan kelompok manusia dari segi aliran masuk, aliran keluar dan pergolakan kelompok semasa kecemasan. Pengelas digunakan untuk mengesahkan keupayaan ciri untuk membezakan data kelas pengecaman aktiviti individu. Eksperimen SBTFD dengan pengelas pepohon keputusan (J48) menghasilkan ketepatan maksimum 99.2% dan kadar negatif palsu 3.3%. Kelas individu diklasifikasikan berdasarkan 7 ciri terbaik yang menghasilkan pengurangan dimensi, peningkatan ketepatan sebanyak 99.1% dan kadar negatif palsu yang rendah (FNR) sebanyak 2.8%. Kesimpulannya, rangka kerja kesedaran-konteks yang telah dibangunkan dalam penyelidikan ini terbukti menjadi penyelesaian yang baik untuk ramalan keadaan individu dan kelompok manusia dalam masyarakat kita.

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LIST OF ABBREVIATIONS

AC	-	Accuracy
AR	-	Activity Recognition
ARAC	-	Activity Recognition Accuracy
BCF	-	Basic Context-Aware Framework
CAM	-	Crowd Abnormality Monitor
CBFS	-	Correlation Based Feature Selection
CCS	-	Crowd Controller Station
CDD	-	Crowd Density Determination
CDT	-	Crowd Density Threshold Condition
CCPFSM	-	Crowd Condition Prediction using FSM
CHIFS	-	Chi-Square Feature Selection
Dsi	-	Flow Direction
EHCAF	-	Enhanced Context-Aware Framework
FD	-	Frequency Domain
FFT	-	Fast Fourier Transformation
FNA	-	False Negative Alarm
FNR	-	False Negative Rate
FEM	-	Feature Extraction Method
FSM	-	Feature Selection Method
HAR	-	Human Activity Recognition
IAR	-	Individual Activity Recognition
IARC	-	Individual Activity Recognition Chain
IBE	-	Individual Behaviour Estimation
IG	-	Information Gain
MI	-	Mutual Information
MRMR	-	Minimum Redundancy Maximum Relevance
MRMR-IG	-	Minimum Redundancy Maximum Relevance-IG

NPV	-	Negative Predictive Value
PBE	-	Participant Behaviour Estimation
RF	-	Random Forest
SBTD	-	Statistical-Based Time Domain
SBFD	-	Statistical-Based Frequency Domain
SBTFD	-	Statistical-Based Time-Frequency Domain
SLR	-	Systematic Literature Review
SPELDCA	-	Stampede Prediction based on ELDA Algorithm
SVT	-	Statistical Validation Technique
TD	-	Time Domain
TDFD	-	Time Domain and Frequency Domain
Vsi	-	Flow Velocity

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CHAPTER 1

INTRODUCTION

1.1 Overview

The field of context-aware computing is one area with active research activities in recent time as the martket presently worth US$120 billion this year (MAM, 2018). The context-aware approach is possible, due to the rise in the number of mobile phone device users across the world and its direct connection to pervasive computing (Diaconita, 2018). Nowadays, it is hard to see an organization where the presence of mobile phone and its application is absent. This state of affairs allows context-aware applications through embedded sensors with direct synchronization of contextual information in the environment (Jung, 2013).

In recent times, different concepts in context-aware research have been proposed with various techniques in other domains. These include education (Gallego *et al.*, 2013; Neves *et al.*, 2014), building automation (Han *et al.*, 2013), health care (Fenza *et al.*, 2012), Library management (Shatte et al., 2014), vehicle safety (Bohmlander et al., 2017) to mention just a few. Disasters are of different types namely: crime, terrorism, fire, and crowd for example. Disaster management is a serious challenge in any organization (Othman and Beydoun, 2013; Othman *et al.*, 2014). Current individual and crowd monitoring approach for individual abnormality, crowd behaviour, and human activity prediction were studied in (Roggen *et al.* 2011b; Zhang *et al.*, 2013; Ramesh *et al.*, 2014). Human activity recognition (HAR), using smartphones equipped with inbuilt sensors, were bases for context-aware mobile computing (Ramesh *et al.*, 2014; Cao *et al.*, 2017).

Individual Activity Recognition (IAR) has proven to be relevant to many domains, including vehicle safety (Bohmalander *et al.*, 2017), health monitoring and fitness tracking (Cao *et al.*, 2017), etc. However, the methods are immature for crowd disaster mitigation, such as a recent stampede that claimed lives of over 100 people in India (Ramesh *et al.*, 2014). Crowd disaster mitigation utilizes IAR to predict the onset of a stampede via the movement of participants and their behavioural patterns using IAR (Ramesh *et al.*, 2014). The problem with smartphone sensor signals is that noise is caused by random information and interference (Faragher, 2012). This is a major challenge because inaccurate and noisy data can hamper detection and recognition (Ramesh *et al.*, 2014).

The hottest research is currently the mitigation of crowd disasters which is the state-of-the-art (baseline) on context-aware computing and wireless sensor network (Ramesh *et al.*, 2014). The existing multi-context fusion is a context-aware framework developed by Ramesh *et al.*, (2014) which utilized a multi-context fusion procedure is treated in this study as a Basic Context-Aware Framework (BCF). The said study on context-aware computing and wireless sensor network i.e. the BCF proposed employed machine learning techniques for individual activity recognition and classification. Ramesh *et al.*, (2014) and Roggen *et al.*, (2011a) used a smartphone as a mobile phone sensing to monitor activity recognition of an individual. The monitored activity is to provide safety control measure to people in case of unforeseen incidents in an emergency situation in a crowd.

However, people find it difficult to ascertain the population that constitutes a crowd (Franke *et al.*, 2015). A crowd is determined by the number of individuals based on space occupied in a particular area at any point in time (Helbing and Johasson, 2007; Franke *et al.*, 2015). According to Franke *et al.* (2015), a crowd is four (4) persons per square meter while six (6) persons are overcrowded. This framework is achieved using a smartphone equipped with sensors to monitor individual behaviour based on activity recognition to make decisions in case of any critical situation. However, the BCF by Ramesh *et al.*,(2014) suffers from the following problems:

i. Inadequate activity recognition accuracy of 92% used for prediction of stampede in a crowd due to classification problem with less effective features.

ii. Unpaid attention to the effect of false negative rate, which often caused high false alarm as the number of people grows exponentially in a crowd for reliable stampede prediction..

iii. Unreliable prediction of crowd disasters with the use of inaccuracy from context information that create false negative alarm with election leader and distributed consensus algorithm for stampede prediction.

iv. Unclear crowd density definition and wrong feedback to victims due to inaccurate context -aware notification which amount to high risk than safety in a crowd disaster situation.

The aforementioned problems bring about the motivation to extend the basic context-aware framework by Ramesh *et al.*, (2014) with an improved feature extraction and feature selection method to improve the performance in terms of accuracy and false negative rate.

1.1.1 Definition of Context-aware Framework

In this study, the context-aware framework is defined as a framework that utilizes contexts such as user (individual) activities, location and time which are hidden information derived from smartphone sensors as a form of data used to monitor the situation in crowd scenarios. In other word context is produced anytime, anywhere by everything and anyone: hence it is volatile and subjective (Denzil, 2014).

The enhanced framework comprises of effective features used to obtain hidden context information with an improved feature extraction and feature selection methods based on individual activity recognition to monitor crowd situation and generate accurate context-awareness sensitization alert to avoid the occurrence of abnormal movement with minimal risk of danger to human lives.

Crowd disaster is usually triggered by inadequate space and individual loss of physiological and psychological control (Ramesh *et al.*, 2014). This could be guided with crowd monitoring by means of context sensing and acquisition of sensor signals using a smartphone in the focus Enhanced Context-aware Framework (EHCAF).

1.2 Background of the Problem

This section presents inaccuracy and false negative alarm problems. The causes of inaccuracy and high false alarm arising from individual activity recognition are discussed. The implication of these problems using context-aware computing with individual activity recognition is described.

1.2.1 Inaccuracy Problem in Activity Recognition: Feature Extraction Methods

Guha-sapri *et al.*, (2015) acknowledged stampede related problems and confirm that 22,765 crowd-related deaths occur from 2005 to 2015 and a financial loss of about US$70.3 billion incurred. Rodrigues (2016) defines human stampede as a disaster caused by massive movement (within a limited space) of individuals in response to a perceived danger. For instance, Italy in June 2017 recorded 1,500 injured persons and Saudi Arabia in July 2016 recorded a stampede of 2,297 pilgrims. Helbing and Mukerji (2012) stated that the incidence of crowd accumulation is inevitable but the effort should be made to put the risk under check.

Fruin (1993) presented Force (F), Information (I), Space (S) and Time (T) as a FIST model and as relevant variables in crowd monitoring and disaster prevention. Davies *et al.*, (1995) adopt Close Circuit Television with pattern recognition but Bouguessa *et al.*, (2015) assert that it lacks a feedback mechanism unless security personnel are attached. Gomez *et al.*, (2009) proposed a Wireless Sensor Network using wireless communication technique but yet, the evolving problems of crowd monitoring systems is still unresolved.

Roggen *et al.*, (2011b) present a crowd behaviour recognition chain method, an Individual Activity Recognition Chain (IARC) which uses mobile sensors data collected from an ensemble of ten users activity. The pattern analysis and the graph is a representation of individuals walking independently, in a group and those walking in two or more groups. The crowd behaviour is obtained by inference. Roggen *et al.*, (2011b) assert that 80% accuracy is sufficient for activity recognition despite IARC limitations in the area of two user data collection and the use of variance as a feature extraction method.

Although they suggested that IARC could be useful in future for crowd disaster prevention but failed to present an empirical proof for the suggestion. These problems in Roggen *et al.*, (2011b) establish the rationale for Ramesh *et al.*, (2014) study. Ramesh *et al.*, (2014) improved upon Roggen *et al.*, (2011b) by adopting context-aware computing and a wireless sensor network to investigate activity recognition accuracy for crowd disaster prediction. Other added activities include standing, fall, jogging, climb down, climb up, and peak shake while standing (Ramesh *et al.*, 2014; Mehrang *et al.*, 2018). The reported results of Ramesh *et al.*, (2014) provide an insight with estimated values for the Time Domain (TD) parameter (mean, standard deviation, root mean square and correlation coefficient).

Fast Fourier Transform (FFT) of the root mean square and correlation coefficient is the Frequency Domain (FD). The FD values were very useful in the feature extraction process. This led to a 92% accuracy result compared to 80% presented by Roggen *et al.*, (2011b). Su *et al.*, (2014) and Cao *et al.*, (2017) observed that the classification accuracy of human activity recognition scheme is relatively low, hence 92% of Ramesh *et al.*, (2014) is not good enough because of the high incidence of false alarm, thus; further research is recommended.

Ramesh *et al.*, (2014) uses four algorithms for participant identification using Smartphone (S) as a node on a sample population of 20, the flow direction and flow velocity of the node S are noted and recorded. Stampede prediction was obtained from the individual behaviour estimation and election leader algorithm. Clogging of real-time simulation of participants on the Crowd Abnormality Monitor (CAM) is based on the Android operating system. Simulation of CAM with a basic context-aware framework for mitigation of crowd disasters was implemented and serves as an improvement over the study of (Roggen *et al.*, 2011b).

Ramesh *et al.*, (2014) assert that an inadequate high rate of False Negative Alarm (FNA) led to inadequate real-time information dissemination and inefficient stampede prediction. Otebolaku *et al.*, (2016) stated that lack of individual effect observations of the feature extraction contributed to the low accuracy observed in Ramesh *et al.*, (2014) but no effort was made to proffer solution to the problem.

The result of Ramesh *et al.*, (2014) has low accuracy performance, high FNA for stampede prediction and the crowd density value was not estimated for individual abnormality detection. These are the problems that affect the efficient stampede prediction in Ramesh *et al.*, (2014). Actually, Anguital *et al.*, (2013a) and Mehrang *et al.*, (2018) suggested feature extraction but the approach was a statistical-based feature extraction method. The effort of Ramesh *et al.*, (2014), a distinct follow up on the work of Roggen *et al.*, (2011b) and the observed problems encountered therein constitute my source of inspiration and motivation in this study.

1.2.2 High Dimensionality of Features Space on Mobile Device in Activity Recognition due to unclear Feature Extraction Methods

In Activity Recognition (AR) and machine learning research, knowing the right features that would be capable of generalizing the classification model in its best form is a challenge (Quesada *et al.*, 2015). It has been observed that the problem also occurs due to unclear feature extraction methods usually employed in AR (Suto *et al.*, 2017). The aforementioned problems emanated from the issue of inaccuracy in AR. The inaccuracy problem in AR, which is yet to be addressed completely is investigated further. However, the likely problem which may occur with an improved statistical-based feature extraction method with time-frequency domain features as earlier stated is the tendency of having redundant features in the feature vector, which could lower the accuracy performance (Attal *et al.*, 2015).

Given this, when the dimensionality of features on the mobile device increases the computational cost also increases exponentially (Holgersson and Akerberg, 2015). Consequently, when the features are less and effective, the processing time and memory utilization of the smartphone device required to monitor and recognize individual abnormality behaviour in a crowd will reduce (Riboni and Bettini, 2011). Therefore, when the number of participant monitors with such device grows as a result of less number of features; then, the battery life of the device will be durable. Overcoming the above problem requires finding ways to reduce the number of features to be considered in this research, using the Feature Selection Method (FSM). Feature selection method for activity recognition has been proposed by Ravi *et al.*, (2005); Lara and Labrador, (2012); Saputri *et al.*, (2014) and Suto *et al.*, 2017 using 24, 9, 21 and 6 features to achieve a corresponding accuracy results of 77.33%, 67%, 93% and 93% respectively with decision tree as classification algorithm.

This study found that with the use of different feature selection techniques and the success recorded across domains which have facilitated early onset detection of dengue fever (Devi *et al.*, 2016), pattern (Wen *et al.*, 2015) and stroke (Gonzalez *et al.*, 2015). This could also help for reliable prediction of crowd disasters in a disaster-prone area if the technique is carefully chosen and introduced to improve upon the existing basic context-aware framework. It has been found that there has been a scarce study that applied or investigated feature selection in AR for individual abnormality monitor; using context-aware approach for crowd disaster mitigation.

The proposed solution will investigate the benefit of Minimum Redundancy Maximum Relevance and Information Gain (MRMR-IG), Correlation-based Feature Selection (CBFS), ChiSquare Feature Selection (CHIFS) specifically in the first stage of this study, as the second method suggested for the second objective to enhance the proposed approach since it was not part of the basic context-aware framework (Ramesh *et al.*, 2014).

1.2.3 High False Alarm for Crowd Condition Prediction due to Inaccuracy with Context-aware issue on Individual Behaviour Estimation

According to Okoli and Nnorom (2007), the human stampede situation is an example of disasters in any nation. The stampede incident which often leads to a crowd disaster is common across the world. The implication of this danger in a disaster situation represents a critical challenge to the national security of any nation. In the study of Fruin (1993), the main causes of mass death and injury worldwide were traced to human stampede (Still, 2014). Early context-aware frameworks by Schilit and Theimer, (1994) and Ravindran *et al.*, (2014) do not consider the use of monitoring individuals using activity recognition in public place to identify possible occurrences of dangers.

Based on the analysis of the previous studies, it was very clear that stampede was the cause of crowd disasters in small or public places (Fruin, 2002; Okoli and Nnorom, 2007, Michael *et al*., 2014). However, the previous studies did not use activity recognition based on the individual to investigate inaccuracy, and the effect of false negative alarm for stampede prediction, consequently it was also not the priority in the existing study by Ramesh *et al.*, (2014). Given this, it suffices that a higher classification performance can help to improve the accuracy used in the existing study.

The cause of unreliable stampede prediction in the basic context-aware framework is the problems of inaccuracy and high false negative alarm arising from high dimensionality of features based on inadequate context information from the sensor signals from a smartphone as presented in Section 1.2. The problems highlighted above are very crucial to the proposed framework towards improving the baseline as the focus in this study.

In recent time, authors have proposed various applications using context-aware framework which includes:

i. CamWAF: Framework for lightweight context-aware mobile applications (Luo and Feng, 2016).
ii. CAAC: Framework for context-aware access control to information resources (Kayes *et al.*, 2017).
iii. Framework for exploiting internet of things for contextAware trust-based personalized services (Otebolaku and Gyu, 2018).

The frameworks were found in different domains due to the importance of context-aware computing and its application across many disciplines. However, none of such context-aware framework for mitigation of crowd disaster was found in the literature to the best knowledge of the researcher. Apart from the work of Ramesh *et al.*, (2014) usually referred to as crowd abnormality monitor for onset stampede prediction in a crowd scenario. The work used activity recognition of individual through a smartphone as a monitoring device to determine the occurrence of abnormal situation among individuals in a crowd. Given this, the current study proposed an enhanced context-aware framework by utilizing the proposed method achieved in Subsection 1.2.2 alongside other algorithms that will be implemented for individual behaviour estimation as the last part of this research. The advantage of the proposed framework is the ability to provide efficient stampede prediction using improved accuracy with low false negative rate to minimize the risk of danger to human life in crowded places. The approach also promises prompt and reliable feedback to likely victims of danger in case of an unforeseen situation with reduced features utilized to improve the BCF by Ramesh *et al.*, (2014).

Most importantly, failure to detect the crowd behaviour at the right time could lead to unnecessary injuries and fatalities (Yassen *et al.*, 2013). Yassen *et al.*, (2013) observed and pointed out that real-time accurate estimation of density in different areas, within the space occupied in a crowd could help to improve the decision-making process. This will provide a more accurate prediction of the crowd dynamics using crowd count in terms of Crowd Density Determination (CDD). The proposed EHCAF will adapt the use of CDD as part of the component suggested as solution presented in this thesis. The CDD will help to determine the inflow, outflow, and crowd turbulence during a critical situation of individual activity recognition monitor in a crowd condition. This is done in addition to other parameters needed for Individual Behaviour Estimation (IBE) in objective 3. The problems addressed in this thesis is summarized in Figure 1.1.

1.3 Problem Statement

Recently, various signal processing techniques are studied to analyse the sensor signals from a smartphone. The use of the sensor signals plays a prominent role, towards representing the hidden information from individual behaviour movement in a

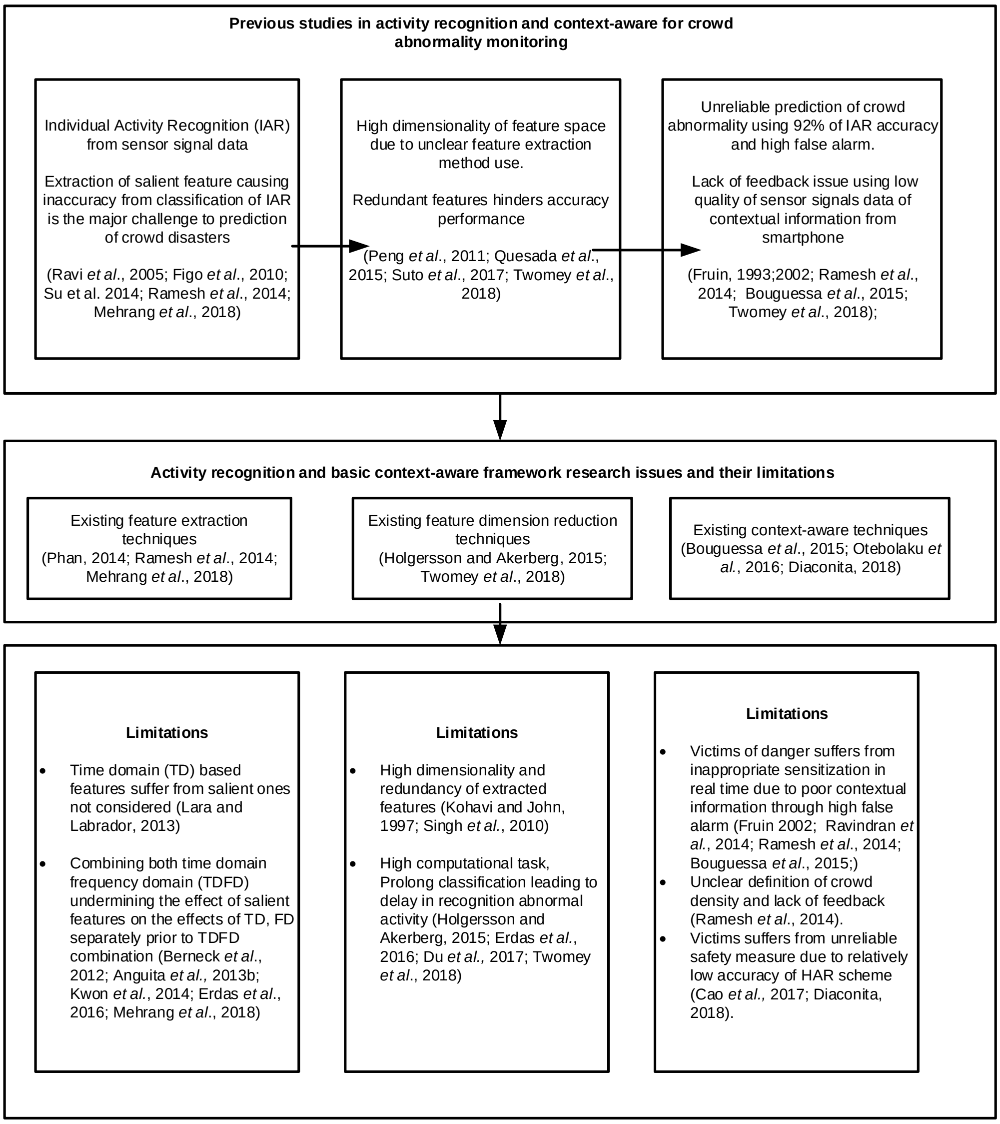

Figure 1.1 The recent research problems in activity recognition.

crowd using context recognition for human activity recognition (Ramesh *et al.*, 2014; Otebolaku *et al.*, 2016). The major drawbacks observed was inaccuracy and hidden information present in the raw dataset from sensor signals. Consequently, the existing feature extraction methods result in not providing accurate information and unsuitable choice of time, frequency domain features that often result in false information, thus, produces the wrong prediction of individual behaviour. Besides, many important extracted salient features are overlooked due to an unclear method of feature extraction used (Suto *et al.*, 2017). This brings about high dimensionality when computation and prediction take place through mobile device since there is no rule guiding the number of features required for any activity recognition, machine learning and data mining researchers (Quesada *et al.*, 2015). The high dimension i.e. any numbers of features could be reduced by filtering technique based on the proper choice of feature selection in activity recognition such as correlation, chi-square and information gain to name a few. After the features have been extracted from the user's context based on raw sensor signals, models can be constructed from these data using artificial intelligence and the traditional machine learning algorithms for individual activity recognition classification. In order to extract the features, different processor speed, battery power on the device may not be sufficient when a number of people increases. As a result of the highlighted problems, less number of effective features is required to minimize the processing time, computational task and classification process (Riboni and Bettini, 2011). Hence, the BCF for crowd abnormality monitor using the classification of individual activity recognition has recently become a common approach in machine learning (Ramesh *et al.*, 2014; Bouguessa *et al.*, 2015). However, results show that it easily suffers from inaccuracy, high false negative alarm and lack of feedback to victims of danger in a disaster-prone situation addressed in this study. Figure 1.2 shows an example of a crowd disaster that occurred in Saudi Arabia with several loss of lives. In the light of the aforementioned incidences, it is desirable to minimize the continuous death occurrence from human gathering in our society.

Figure 1.2 Cross-section of casualties reported in Mina stampede during hajj september, 2015 (Jola, 2015).

How can the accuracy performance of activity recognition in basic context-aware framework be improved for efficient prediction of individual and crowd condition with the low false negative rate? In order to overcome the aforementioned problems, the study provides an answer to the main Research Question (RQ) through the sub-questions as follows:

i. In what forms are sensor signals data of individual activity from smartphone recognized?
ii. How can the use of feature extraction methods adequately represent hidden context information of sensor signals from a smartphone for classification of individual activity recognition to improve on the accuracy performance?
iii. How accurate are the existing classifiers?
iv. Which feature selection based on feature extraction methods can reduce high dimensionality of features on the mobile device, as well as remove redundant features to improve accuracy and reduce false negative rate performance for individual and crowd condition prediction?
v. What other parameters can be utilized with features selected in the basic context-aware framework for individual and crowd condition prediction?

1.4 Research Aim

The study aims to develop an enhanced context-aware framework (EHCAF) using relevant feature sets of activity recognition to improve accuracy and reduce false negative rate performance that is capable of providing an efficient prediction for individual and crowd condition.

1.5 Research Objectives

i. To propose an improved feature extraction method using a statistical-based time-frequency domain that can represent hidden context information from smartphones sensor signals for individual activity recognition in order to improve accuracy for individual and crowd condition prediction.

ii. To propose a feature selection method, which is a sub-component of individual behaviour estimation based on feature extraction to reduce the dimensionality of features on a mobile device with an improved accuracy to reduce false negative rate performance for individual and crowd condition prediction.

iii. To propose an enhanced context-aware framework using the selected features and individual behaviour estimation to provide a reliable prediction for individual and crowd condition.

1.6 Research Scope

The extent of this study is limited to the following:

i. The proposed study focuses on studies related to individual activity recognition chain, crowd behaviour recognition chain, inaccuracy in activity recognition, high dimensionality issue, feature; extraction, selection and classification techniques, context-aware, crowd condition and prediction.

ii. Statistical based time-frequency domain methods are applied as feature extraction in a crowd scenario; while minimum redundancy maximum relevance and information gain, correlation based and chi-square are employed as feature selection methods.

iii. Decision tree (J48), Random Forest (RF), Sequential Minimal Optimization (SMO), and Naive Bayes (NB) are employed as classification algorithms. The k-means, Kalman filter algorithms for Flow Velocity (Vsi), Flow Direction (Dsi) determination and pairwise behaviour estimation are adopted from the literature based on Euclidean distance and vincenty formula are applied for individual behaviour estimation in the proposed Enhanced Context-Aware Framework (EHCAF).

iv. Evaluation of the approach is based on Accuracy, Precision, Recall, F-Measure, Specificity, Negative Prediction Value, Mathew Correlation Coefficients, Macro-average and false negative Analysis of variance and paired sample t-test statistical tests were applied for validation of results. The comparison was done with Crowd abnormality monitor (CAM) by Ramesh *et al.*, (2014) as Basic Context-Aware Framework (BCF).

v. Activity recognition of individual such as walking, standing, fall, climb down, climb up, peak shake while standing, jogging and still widely used are employed as simple activity type (Lara and Labrador, 2013; Sztyler and Stuckenschmidt, 2016). What if the non-simultaneous activity assumption is out the scope of this study.

vi. Implementations of algorithms are done using Python and WEKA (Hall *et al.* 2009 and WML, 2018). Software development and a simulation of crowd movement behaviour using the toolbox, ground truth of positive and negative dataset for stampede evaluation and validation, stampede prediction or crowd disaster prediction are out of the scope of this work.

vii. One public dataset of activity recognition from the UC Irvine machine learning repository UCI, (2015) has been used with real-time sensor dataset collected in this study with developed android context-aware mobile application.

1.7 Significance of the Research

The crowd is the coming together of people in a place. This same crowd is a common event in public, private and government organizations of any nation. However, the safety of the people is very important to the growth and the development of any nation across the world. Therefore, the priceless nature of the people cannot be overemphasized, as the safety control measure technology or system as a step to minimize risk (HSE, 2018). This research is proposed to give an insight to the inaccuracy and high false negative alarm effects on a context-aware framework using activity recognition. The insight was done through discussion on how to improve the performance of accuracy to reduce the false negative rate, especially within the context of inaccuracy and high dimensionality of feature space in activity recognition.

The issues regarding inaccuracy and high dimensionality of feature space for stampede prediction in a crowd are presented in this research. This study shows that Enhancement of Context-aware Framework (EHCAF) with feature selection method, can improve the accuracy of activity recognition and reduce false negative alarm significantly. It serves as an alternative to other techniques found in this domain in literature. It will also, facilitate risk of danger minimization (reduction of false negative rate) during an emergency in a crowded place. The proposed EHCAF of prediction for individual and crowd condition if implemented can be useful in Hajj, sports complex, airport, shopping complex and praying ground such as mosque, churches and concerts to mention a few.

1.8 Summary and Organization of the Thesis

The chapter has described the motivation of the research by presenting the background of the problem and also outlines the purpose and aim of the research. The chapter also presented the possible contributions of the research. The remaining part of the thesis are briefly discussed as follows:

Chapter 2: Literature reviews discuss past and current studies in the research area related to context-aware computing, activity recognition, feature extraction and selection methods utilized, sensor fusion with an emphasis on crowd disaster are discussed. The strengths, weaknesses of existing basic context-aware framework's gaps and related study were highlighted in the chapter.

Chapter 3: Research methodology presents the research methodology flow used in this study. It consists of the general overview of the research in addition to the steps required to carry out this research in an orderly form. It also contained a description of the datasets acquired for the experimental purposes of the study. Chapter 4: Presents first objective where feature extractions were explored in the chapter for the enhancement of activity recognition accuracy using statistical-based time-frequency domain features for classification of activity recognition for individual and crowd condition prediction. Corresponding results and evaluation are also presented in the chapter along with a statistical test to confirm the results.

Chapter 5: discuss the second objective as the newly proposed feature selection method based on the minimum redundancy maximum relevance, information gain, correlation and chi-square separately. The objective helps to reduce features to the best seven relevant features. Four classification algorithms were utilized for individual activity recognition. It covers the experimental setup, relevant discussions, and comparisons of the method. The statistical tests were presented to validate the results.

Chapter 6: Enhanced context-aware framework. Addresses the third objective of the research. It presents the development of an improved context-aware framework by utilizing the individual behaviour estimation based on each class (activity) of an individual with feature selection method for higher activity recognition accuracy, and low false negative rate achieved in objective 2. The detail of additional parameters derived from individual behaviour estimation based on algorithms adopted from the literature is presented. The benchmark of the proposed and existing approaches was also presented in this chapter. The result is validated using a statistical test.

Chapter 7: Conclusion and future works. Concludes the research, highlights the list of contributions, states the limitations of the proposed approach, and shows the objectives 1, 2, 3 deliverables of the thesis and presents recommendations for future study.

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